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ABSTRACT
Storylines are plausible descriptions of past or future events and can be used to characterize uncertainty through discrete possible futures. They thereby bridge the gap between global-scale future projections and local-scale impacts, providing decision-makers with useful information about potential impacts in multivariate systems despite large swathes of missing data. Here we demonstrate the storyline approach using the case of household food security in the Caprivi region of Namibia, an example of a complex system with multiple interacting drivers. We develop a network characterizing influences on household food security, highlighting drivers that are affected by the local weather (with climate understood to constitute the collection of possible weather states). The network is used to understand the storyline leading to household impacts in 2013–14, a consumption year affected by flooding, and the effects of a range of interventions across wealth groups. Counterfactual storylines are also developed to characterize potential impacts under different local and national conditions. Through this we demonstrate how a storyline approach can embed local contextual information to provide decision-makers with comprehensible and assessable information about possible futures and interventions. We highlight the importance of identifying common drivers, in this case the local weather, in producing plausible impact storylines.

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1. Introduction

Top-down climate risk assessments often lead to a 'cascade of uncertainty', where the uncertainty range expands at each step, from the emission scenario to the climate model, regional scenario, impact model, local impacts and adaptation responses (Wilby & Dessai, 2010). These compounding uncertainties can potentially render the local-level information un-actionable as the benefits of action are swamped by the uncertainties. The logical flaw in such an approach is that it ignores the structural, or correlated nature of the uncertainty (Shepherd, 2019). Storylines provide an alternative to this conventional probabilistic approach, characterizing uncertainty instead through a set of distinct possible pathways. Storylines are physically self-consistent descriptions of past events or plausible future events (Shepherd et al., 2018) that are supported by quantitative analysis. They provide a way of bridging the global prediction scale and the local impact scale through understanding the driving factors involved in an event, particularly when dealing with complex, multivariate problems where there is poor data availability (Shepherd et al., 2018).

An example of such a complex problem is that of understanding the impact of climate on local food security in rural communities in Africa. Food security is defined as when 'all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life' (FAO, 1996), and involves farmers, traders, governments and donors, among other actors. Food security is thus a complex system with multiple interacting drivers, both environmental and socioeconomic (Vogel & Smith, 2002), which are uncertain both in themselves and in how they interact (Ingram, 2011). These drive insecurity over different timescales, with chronic stressors such as poverty, conflict and poor market access compounded by short term shocks such as food price increases or reductions in regional cereal availability (Misselhorn, 2005). This can make analyzing the impacts of a particular driver such as climate challenging, as it is interconnected with other environmental and socioeconomic drivers (Connolly-Boutin & Smit, 2016). Climate change is likely to affect not only food availability directly through reductions in yields across much of Africa (Lobell et al., 2008; Parry et al., 2005), but also food access due to reductions in household income, increasing population, increasing food prices and impacts on supply chains, and food utilization through impacts on drinking water access and health (Brown et al., 2009; Brown & Funk, 2008; Gregory et al., 2005; Lobell et al., 2008; Parry et al., 2005; Schmidhuber & Tubiello, 2007; Wheeler & von Braun, 2013). Top-down approaches to model climate change impacts often lack local contextual information (Wheeler & von Braun, 2013), and data to predict food security, such as market prices, are often not available at the high spatial and temporal resolutions required (Lentz et al., 2019).

In this paper we will develop and discuss food security storylines for the Caprivi region of Namibia, to demonstrate how the storyline approach can provide information on local impacts

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even in the presence of large uncertainty. To ensure the storylines are grounded in the local context, they are developed with data generated using the Household Economy Approach (HEA, Seaman et al., 2014). The HEA draws on entitlement theory from Sen (1981) to understand the food security system at the household livelihood level. Sen defines entitlement as 'the set of alternative commodity bundles that a person can command in a society using the totality of rights and opportunities that he or she faces' (1984, p. 497). The HEA models a household's ability to get food and other goods within the framework of rights and opportunities, expressing Sen's theory in a practical way for rural households. This does not depend just on the availability of the goods. Instead, whether a household can access enough food is modelled from a household's own food production, their cash income, assets and the market prices. In this way a logically complete picture of a household's economy is produced from which impacts of shocks can be assessed. Shocks might include a specific crop being affected by poor weather conditions or pests leading to reduced yield, or the price of a commodity increasing on the local market. The methodology is based on focus group interviews to provide enough information to model the impacts of shocks across households, while ensuring data collection costs remain reasonable.

The HEA is typically used in policy contexts to generate storylines using different values of uncertain variables, such as future crop production or food price. The storylines show the impacts on household food access and can be used to simulate the cost potential interventions such as food and cash distribution, market support, or tax reductions. The HEA is used operationally in countries across southern Africa, with results providing information for governments to address the impacts of year-to-year shocks, as well as develop scenarios of long term climate impacts on livelihoods (Luxon & Pius, 2012; Seaman et al., 2014). This is therefore a context where the use of storylines to characterize possible futures is already widely used by policymakers to initiate and guide interventions (e.g. FEWS NET, 2020; Government of Malawi, 2005, 2016; Holzmann et al., 2008; Seaman et al., 2014), with governments and donors finding the information comprehensible and assessable.

Here, we work from the household economy dataset for Caprivi, Namibia, to show how HEA-based storylines can be developed to consider climate risk, where we understand climate to be the collection of possible weather states. We use a storyline of a historical event along with counterfactual storylines, which might have occurred given different circumstances, to understand how the multiple drivers of food insecurity interact. We identify key drivers of potential local impacts, and show how different actions would mitigate those impacts. This example is used to demonstrate both the process of developing storylines, and the useful insights that can be gained from applying a storyline approach, for the wider climate and development community, as well as policy implementers.

2. Approach

2.1. Storyline approach

Storylines can be used to understand the most important driving factors of an impact to improve risk awareness, combine climate change with other relevant factors to strengthen decision-making, partition uncertainty, and explore the boundaries of plausibility (Shepherd et al., 2018). In particular, epistemic uncertainty, which is deterministic in nature, can be represented using a discrete set of storylines (Shepherd, 2019). Epistemic uncertainties are due to a lack of knowledge, and may be reduced with increased understanding, for example by including additional processes in a model representing a system (Beven, 2016; Beven & Young, 2013). On the other hand, aleatoric uncertainties arise from random variability, for example random measurement errors, and can be represented by probabilities (Beven, 2016; Beven & Young, 2013).

The key to reconciling storyline and probabilistic approaches to uncertainty is causal networks, as both can be considered within this one framework (Shepherd, 2019). Causal networks are directed acyclic graphs (Pearl, 2009) depicting the causal influences between elements in a network. They are developed using data or expert knowledge, with storylines generated as pathways through the network. Causal networks are used in many fields to understand the drivers of different impacts, including specifically as Bayesian networks (e.g. Flores et al., 2011; Marcot et al., 2006; Pollino et al., 2007; Villordon et al., 2010). A Bayesian network represents a set of variables and their conditional dependencies through probability distributions for each variable, conditional on the states of the other variables.

Storylines can look similar to the outputs of scenario planning, which has been used across many disciplines for a number of years, including within adaptation planning for climate risks (e.g. Chaudhury et al., 2013; Dessai et al., 2005). Storylines have also been used to represent possible future climate risks; for example, Ranger and Niehörster (2012) generated scenarios of wind-related property losses in Florida from possible future changes in hurricane hazard. Workshops in African cities have generated climate risk narratives of past and future events, from the climate context through to impacts and possible responses in each location (Cornforth et al., 2019; Cornforth & Myers, 2020; McClure, 2018; Scott et al., 2018).

The approach taken here is therefore part of a wider movement using networks and storylines to articulate plausible futures based on explanations, or causal accounts, of past events, and thereby to identify actions associated with future adaptation pathways (Lloyd & Shepherd, 2020). We are not taking a Bayesian network approach here because, as is the case for many other 'real-world' complex systems, we do not have sufficient quantitative data to interrogate links between drivers of food security, identify which are causal, and calibrate a model. Typically, data is unavailable over long time periods for some drivers, and other drivers are not easily quantifiable. Instead, we use the development of a network and knowledge of the food security context as a framework for a deductive approach to understand the data we do have available (Lauritzen & Spiegelhalter, 1988), and a tool to investigate possible pathways and impacts.

2.2. Case study: Caprivi, Namibia

To demonstrate the storyline approach we use the example of food security in Namibia. Namibia was chosen because, as an upper middle-income country (World Bank, 2019), it has a more structured economy and response to national food insecurity compared with many other sub-Saharan African countries. Data was collected in Namibia using the HEA methodology (Seaman et al., 2014) in 2008–2009 to characterize the economy of a set of 'typical' households for the area.

The Namibia Vulnerability Assessment Committee (VAC) first divided the country into livelihood zones (zones where households obtain their food and cash income by broadly the same means) in 2008, using a combination of expert knowledge, literature, and physical, economic and human maps (Office of the Prime Minister, 2008). Here we focus on the Caprivi Lowland Maize and Cattle livelihood zone, situated in the northeast of the country (Figure 1), and vulnerable to river floods (Office of the Prime Minister, 2010a).

Focus group interviews across villages in each livelihood zone in 2009 classified wealth groups in each village, based on productive assets such as land, livestock and labour sources. Interviews also gathered information on the seasonality of crops, market access and coping strategies. In Caprivi, focus groups were held in eight villages, with four wealth groups identified. It was estimated that 31% of households fall into the 'Very Poor' category, 39% are 'Poor', 22% are 'Middle' and 8% are 'Better-off'. A further 26 focus groups were then carried out with members of each wealth group in each village, to capture detailed information about household food and income sources and expenditure patterns. Focus groups were semi-structured interviews, structured around a classification of food and cash income sources, with data checked after each interview for consistency both internally (e.g. amount of land worked is consistent with the crops produced) and with the observed standard of living and physiological food requirement. Further detail on how data is collected using the HEA can be found in Seaman et al. (2014, Supplementary material). In Caprivi, data collection focussed on recall of the agricultural year 2007–08, which was a relatively normal year in the region (Office of the Prime Minister, 2010b). Data were combined to produce a food budget for a year for a typical household in each wealth group, based on food grown, sold and bought, and other income sources and expenditures.

From these budgets, the HEA can be used to model what would happen in years when there are shocks, and whether a household in each wealth group would be able to access enough calories through what they produce and can purchase. For this analysis, a required minimum calorie intake of 2100 kcal/person/day is assumed, as derived from information given by the WHO (1985). This is a figure used operationally to measure access to enough food energy, as a best estimate for populations of developing countries. However, people can survive on less than 2100 kcal/person/day, and in some settings a lower value might be appropriate. Based on the data collected in 2008–2009, the VAC produces reports each year documenting predicted food security outcomes. We base our analysis on the report for consumption year 2013–14 (Namibia VAC, 2013), as it was a year affected by flooding.

2.3. Developing food security storylines for Caprivi

Using the HEA data and VAC reports, we begin by identifying the drivers associated with household food security, and mapping the links between them pictorially. We start from understanding the factors influencing local household food security and then consider larger-scale drivers of these, in order to ensure all local factors are included. We use the network diagram to investigate the unfolding of a historical event, mapping the drivers and impacts onto the network to provide a storyline about the past within the causal network framework. We also consider counterfactuals: what might have happened had the context or decisions made been different? In this way, we demonstrate how HEA data can provide a quantitative basis for identifying plausible storylines and policy options.

To understand the storyline of a historical event we use information available on how the drivers of food security were changed in that year and apply these to the local household data to model the impacts. We consider this within the context of the food security network to understand the effects of both local and remote drivers. To consider counterfactual storylines, we make assumptions on the states of drivers and apply these to the local household data. The benefit of this approach is that we can make assumptions about drivers where we do not know their future state, and consider a set of possibilities, or investigate how impacts in a past event might have changed had a driver been in a different state. We can specifically investigate counterfactual storylines involving potential interventions, allowing us to draw inferences about their impacts. Considering these in the context of the network diagram helps us ensure that any assumptions made are plausible, based on our understanding of how drivers relate to each other.

3. Results

3.1. Household economies in Caprivi, Namibia

Figure 2 shows the sources of households' food and cash income in Caprivi in the baseline year (2007–08), from focus group data averaged across each of the four identified wealth groups. Food (not including purchases) is shown as a percentage of 2100 kcal/person/day. Maize is an important food source for all wealth groups, with sorghum and millet also consumed by all. Cows' milk consumption increases with wealth while Very Poor and Poor households have a higher dependence on payment in food for farm labour. Households in all wealth groups also purchase food with their cash income, and both Very Poor and Poor households require purchased food if they are to reach 2100 kcal/person/day. Better-off households typically earn cash incomes of more than three times that of Very Poor households, with income from sale of cows' milk, cattle, maize and fish increasing with wealth. Very Poor and Poor households are more dependent on pensions and safety nets, along with farm (weeding, harvesting) and off-farm (construction, domestic, herding) labour income. Households in all wealth groups also earn some casual income, through the selling of reeds, poles, thatching grass and alcohol.

Figure 3(a) summarizes the drivers of a household's economy in an agricultural year as nodes in a network, taken as the income and expenditure categories identified through the focus group interviews: crops, livestock, fishing, labour, other

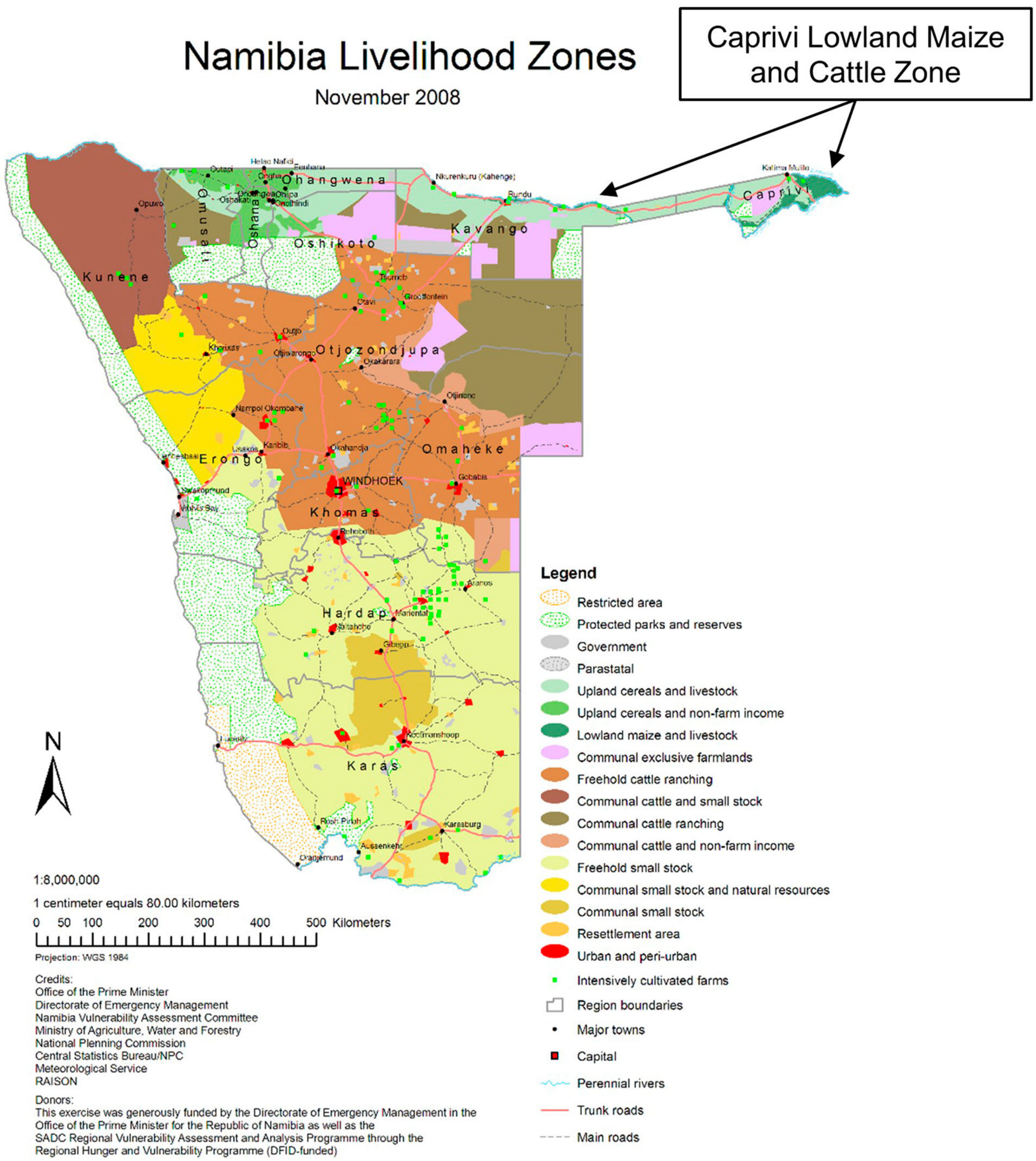

Figure 1. Namibia Livelihood Zones. Caprivi Lowland Maize and Cattle Zone is shown in dark green. Based on a figure from the Office of the Prime Minister (2010a).

income, and expenditure on staple food, other food and livelihood protection. Livelihood protection expenditure includes costs to maintain the standard of living, such as medical, schooling, clothing, livestock (drugs, water and restocking), and crop (seeds and fertilizer) costs.

These drivers are not all independent. One factor affecting multiple drivers is the local weather (here taken as the weather across the Caprivi region). Using understanding from the focus groups we can map out how this can affect multiple elements of a household's economy (Figure 3(b)). The local weather directly affects a household's crop production and livestock, impacting what they can consume and sell, but also affects the availability of local farm labour across Caprivi, such as harvesting work.

The main staple foods sold on markets in Caprivi are locally grown maize and imported food items (Office of the Prime Minister, 2010a). The staple food price is in part affected by the local weather conditions, as market prices will increase if local cereal availability is lower due to poor production and more has to be transported from elsewhere in Namibia. However, in Namibia, a large proportion of cereals consumed are imported (around 50% in a normal year, Office of the Prime Minister, 2010a) so prices are also driven by the international market.

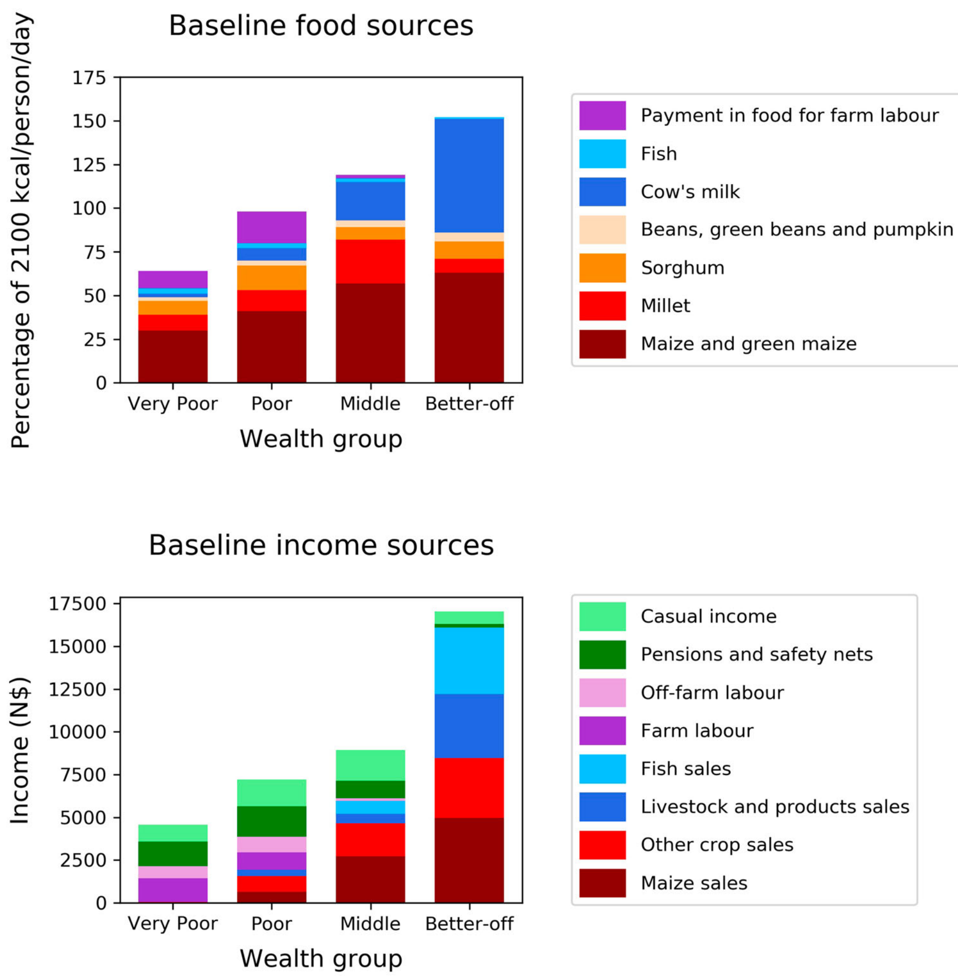

Figure 2. 2007–08 baseline food and income sources for households in the Caprivi region of Namibia for the four wealth groups. Food sources (not including purchases) are shown as a percentage of 2100 kcal/person/day; income is in Namibian Dollars.

Other income sources such as off-farm labour and pensions are not directly affected by the weather, and while there may be some effect on availability of fish for consumption and sale this is not considered here. To maintain their calorie consumption level, if possible a household will react to shocks in the system. For example, if a household's crop production is reduced, they will need to purchase more food, and so may need to increase cash income in other areas such as off-farm labour.

3.2. Storyline of 2013–14 consumption year

We use the study of a historical event (2013–14 consumption year) to demonstrate the process of producing a storyline in the context of the local food security network and evaluating the impacts of possible interventions. Table 1 shows the changes in production leading up to the 2013–14 consumption year and predicted changes in prices (as of May 2013), relative to the baseline data (2007–8), from the Namibia VAC (2013). The 2012–13 growing season leading up to this was characterized by prolonged dry spells and erratic rainfall across much of Namibia (Namibia VAC, 2013), and in the Caprivi region many crops were destroyed by floods associated with high water levels in the Zambezi river (IFRC, 2013).

Production in Caprivi was poor across all the major crops and there were predicted reductions in selling prices for maize and cows' milk and the availability of income from harvesting labour, self-employment and petty trade (Table 1). Because we have data on these observed impacts on food production, prices and labour, we do not need to know the detailed weather conditions leading to these or how to model the links from the weather for the storyline. The low maize selling price, despite low production, may have been due to low purchasing power, or drivers external to the Caprivi region, as food availability also depends on releases from strategic reserves and imports from South Africa. Staple food purchase price was expected to be 35% higher than in a normal year. There were however estimated increases in pensions and cattle sale prices. Availability of local off-farm labour (primarily construction labour) was predicted to increase in response to the poor production to provide income and boost purchasing power for maize.

Figure 4(a) depicts the changes in nodes in the household economy network in 2013–14 that have links to the local weather. We focus here on the weather-related links over the previous growing season, and regard other impact-relevant factors as contingent. While crop production could also have been affected by pests or access to seed and fertilizer, we assume the

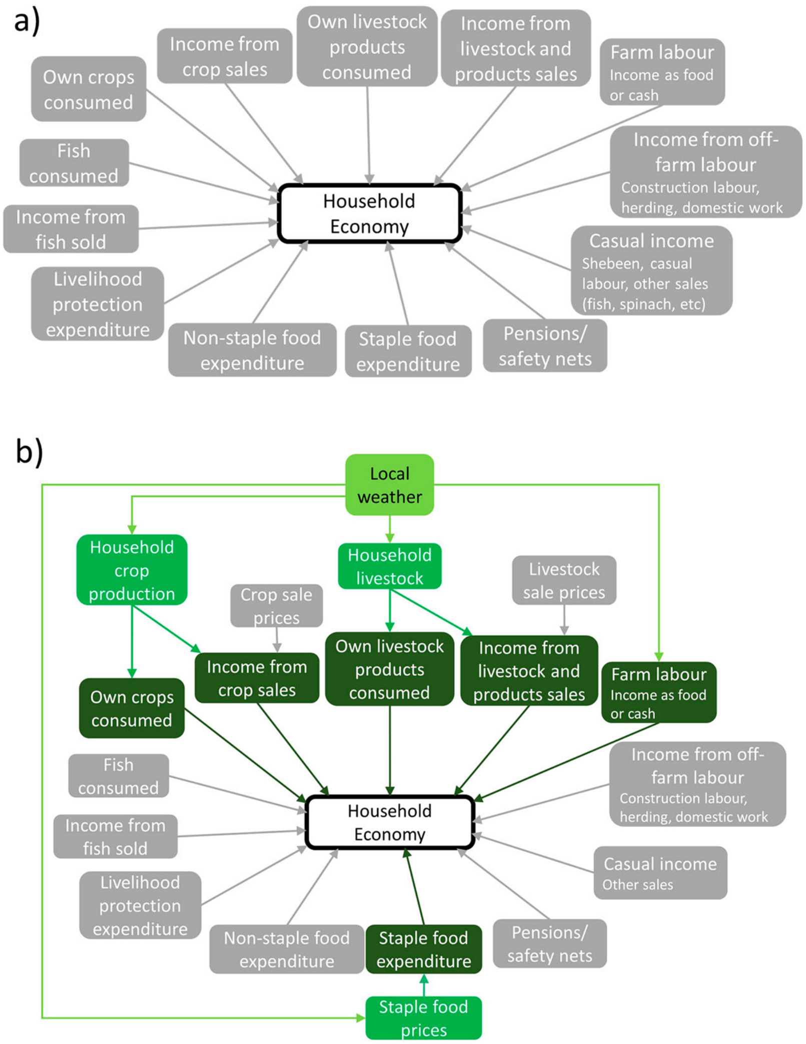

Figure 3. Network diagram illustrating the components affecting a household's economy in the Caprivi region of Namibia. (a) the first level drivers, (b) including the links from the weather.

poor weather had the greatest influence. On the other hand, livestock stocks were reduced by disease and recurrent drought (Namibia VAC, 2013), so we assume the weather immediately preceding 2013–14 had a much smaller influence, and remove the direct link. While we have made these assumptions for simplicity, other assumptions may also be valid and could be used to produce alternative storylines to understand food security impacts under different conditions.

In the HEA household budget calculation, we change incomes and expenditures from the baseline values of 2007–8 by the percentages observed in 2013–14 conditions (Table 1). Calories are totalled for each food type consumed, and any cash income is converted into staple food (maize) calories via the staple food price. We then examine incomes as calories per person per day across the wealth groups, as shown in Figure 4(b). We have assumed no increase in off-farm labour availability but assess the impacts of this later.

Two thresholds are shown in Figure 4(b), which are used to analyze a household's vulnerability when data from HEA studies is applied in policy contexts: a survival threshold and a livelihood resilience threshold, defined for each wealth group. A household reaches its survival threshold when it can meet a minimum calorie intake (taken as 2100 kcal/person/day, as discussed in section 2.2) and purchase some vital non-food items (matches, salt, candles, firewood, and water for human consumption). A household reaches its livelihood resilience threshold when it can additionally afford its livelihood protection expenditure (described in section 3.1). While these thresholds do not exist in real life (for example, a person will survive on less food if they have to, although this is likely to have detrimental effects on their health), we use them here to allow us to compare impacts across the wealth groups. Both thresholds are shown as their calorie value to facilitate comparison, although these include non-food purchases which are converted into a calorie equivalent via the staple food price.

Survival thresholds increase with wealth as non-food essentials such as firewood are divided between the number of people in the household, which decreases with wealth (7 in Very Poor and Poor households, 6 in Middle, 5 in Better-off). Livelihood resilience thresholds increase with wealth as better-off households need to spend more to maintain their level of livelihood through, for example, higher livestock restocking, labour, school and medical costs. We assume a household will make rational decisions with their food and cash to meet these thresholds where possible. All wealth groups except the Better-off would fall below their livelihood resilience thresholds with the conditions in 2013–14, and the Very Poor would additionally fall below their survival threshold.

The Namibia VAC (2013) suggested a number of interventions to support households over the 2013–14 consumption year: cash transfers, food transfers, livelihood support (seeds, fertilizers and animal drugs distributed or subsidized), income generating activities (off-farm) and waivers of expenditure on basic services (education and health costs). Table 1 shows how we change incomes and expenditures in the budgets to assess the impacts of these interventions. Doubling the off-farm income available is shown to be particularly beneficial to Poor households (Figure 4(b)), whereas Middle and Better-off households earn very little from construction labour in a normal year so the increase in their income is smaller. (They may however take up extra off-farm work if it is available, which is not taken into account here.) Reducing livelihood expenditure through support (removing expenditure on seed, fertilizer and animal drugs) and waivers (removing expenditure on education and health) has a greater effect on the richer wealth groups, who typically spend more on these outgoings. Even including all three of these measures (extra off-farm work, livelihood support and waivers), the Very Poor, Poor and Middle wealth groups remain below their livelihood resilience thresholds, and the Very Poor remain below their survival threshold. For these households to meet these thresholds, this gap would need to be filled by the cash and food transfers also suggested. The interventions implemented by the government in this year were support for purchasing seed and hiring tractors for ploughing, and a zero rating tax policy for basic commodities to reduce prices, along with relief food assistance. Households may also have employed some of their typical coping strategies, such as increasing fish sales, buying cheaper foods, or receiving gifts of food or cash (Office of the Prime Minister, 2010a).

Table 1. Impacts and estimated prices and labour availability in 2013–2014, and other conditions to be modelled.

	Factor in household economy	Condition relative to normal (100%)
2013/14 Conditions	Millet production	15%
	Maize production	14%
	Beans production	6%
	Sorghum production	10%
	Maize sale price	19%
	Cattle sale price	113%
	Cow's milk sale price	60%
	Staple food purchase price	135%
	Labour: cultivation	100%
	Labour: harvesting	37%
	Labour: local (Off-farm labour)	100%*
	Self-employment	61%
	Petty trade (Other income)	61%
	Pensions and safety nets	123%
	Changes to 2013/14 conditions	
Interventions		
Off-farm labour	Off-farm labour	200%
Livelihood support	Seed, fertilizer and animal drug costs	0%
Basic services waivers	Education and health costs	0%
Counterfactual Storylines		
Good local weather	All crop production	100%
	Farm labour (cultivation and harvesting)	100%
Normal staple food price	Staple food purchase price	100%

*Given as 200% by the Namibia VAC (2013), however this assumes an increase in response to the other conditions so is modelled as a separate intervention here.
Note: Percentages of normal prices and crop production in 2013-14 are from the Namibia VAC (2013).

3.3. Counterfactual storylines

Having modelled the impacts in 2013–14 and the suggested interventions, we can also investigate other counterfactuals: what would the impacts have been had the conditions been different, or had different decisions been made? Counterfactual storylines are based on assumptions about what could happen in a future pathway of events. Assumptions are made explicitly and allow us to investigate impacts in cases where data is not available to know the states of all variables in a system. The impact of different assumptions can be assessed by looking at storylines of each case.

In the historical storyline, floods destroyed crops, affecting both food and farm labour availability. The Caprivi region is vulnerable to annual flooding from its nearby rivers, along with irregular rainfall and dry spells (Office of the Prime Minister, 2010a, 2010b, 2011, 2012, 2014). How would household budgets in 2013–14 have been different if the weather had been good for farming? With our understanding of the network and which parts of the budgets are directly affected by the weather, we look at these impacts: we increase crop production and farm labour availability to 100% (normal baseline conditions, as shown in Table 1) as these are directly affected by the local weather, but keep the other network nodes unchanged. By so doing we maintain the assumption made earlier that the original crop production decreases were due to the poor weather, but the livestock decreases were not, and we further assume that good weather (from the farming perspective) remains possible within the present climate. We keep the off-farm labour availability at normal levels, so as not to include any increase in response to poor food production. Staple food prices are kept at 135%, under the assumption of a storyline where this price increase is driven by external factors (an alternate storyline could consider the case where food prices were brought down with the increased local food production). This is summarized in the network in Figure 5(a).

Figure 5(b) shows the additional income above that of 2013–14 if we make these assumptions of good local weather. This greatly increases households' ability to access food through both their own crop consumption and purchases with cash from crop sales and farm labour. All except the Very Poor would have enough income to maintain their livelihood levels, while the Very Poor would have enough to be above their survival threshold. This counterfactual storyline is plausible, and so represents conditions policymakers could be faced with in the future. This analysis provides the opportunity to consider the decisions which would need to be made in that case, which would likely be options to support the Very Poor households.

Another major driver of reduced incomes in 2013–14 was the 35% increase in staple food purchase price, driven by an increased demand for market purchases. National cereal

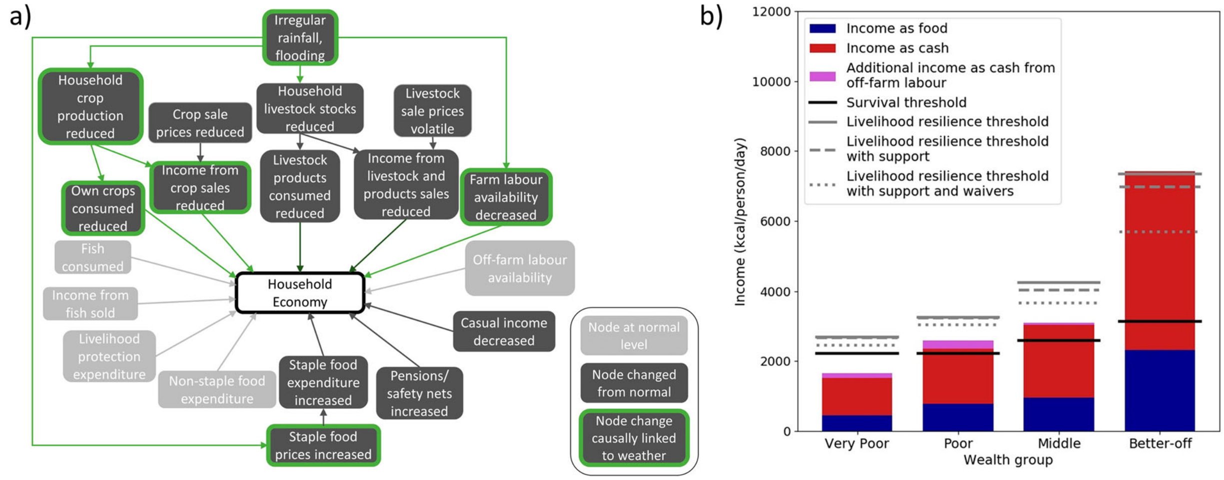

Figure 4. 2013–14 storylines. (a) impacts in 2013–14 shown on the network diagram, showing drivers at normal levels, changed from normal, and where changes are causally linked to the 2012–13 weather conditions. Where changes are not causally linked, the contingent factors are regarded as more important than the 2012–13 weather conditions. (b) resulting incomes and survival and livelihood resilience thresholds for the different wealth groups in 2013–14, along with effects of suggested interventions. Incomes are shown per person per day divided into calories from income directly as food (own crop and livestock production, gifts as food, payment in food) and cash income converted into its calorie value.

production was estimated at 27% lower than normal, and 43% lower than the previous year (Namibia VAC, 2013). Maize prices on the South African Futures Exchange (SAFEX) market were above average throughout the consumption year, and particularly in the first few months of 2014 ahead of the next harvest (FEWS NET, 2014), indicative of higher import prices. Had the national or international weather conditions, and therefore crop production, been different, prices for staple cereals in Namibia may have remained at normal levels. We can model the impacts this would have had on households in Caprivi, illustrating a storyline where local weather conditions and crop production were still poor but staple prices were normal due to good national maize availability (Figure 6(a)). We keep other nodes the same as in 2013–14, under an assumption that only factors external to Caprivi affected the prices and local conditions were unchanged, but use normal off-farm labour availability so as not to assume any increase in this in response to local conditions (Table 1).

Figure 6(b) shows that with normal staple food prices, cash income in terms of calories would increase compared to 2013–14, as the same amount of cash would purchase more staple food. However, the thresholds would also increase as the calorie value of the cash component of these would increase. This counterfactual storyline could occur in reality if the weather conditions were poor in Caprivi but good across the rest of the country, and it also illustrates the impact of a possible policy intervention. Staple food prices could be reduced to normal levels if they were subsidized by the government and this analysis shows policymakers what the impact of this would be. On its own this intervention would not bring Very Poor, Poor or Middle households to meet their livelihood resilience thresholds, but this could occur when combined with other interventions. However, it would help bring Very Poor households much closer to their survival threshold than the off-farm labour, livelihood support and waiver interventions recommended previously. Comparing the two counterfactual

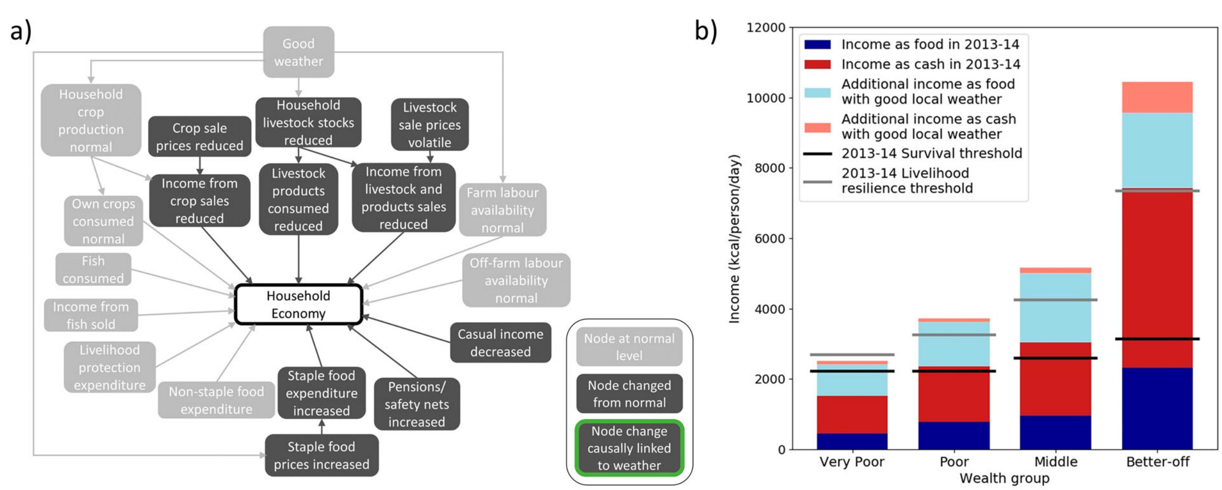

Figure 5. Good weather counterfactual storyline. (a) network diagram as in Figure 4(a) but for the counterfactual storyline of good weather, (b) incomes and survival and livelihood resilience thresholds as in Figure 4(b) but with the effect of local crop production and farm labour being at 100%.

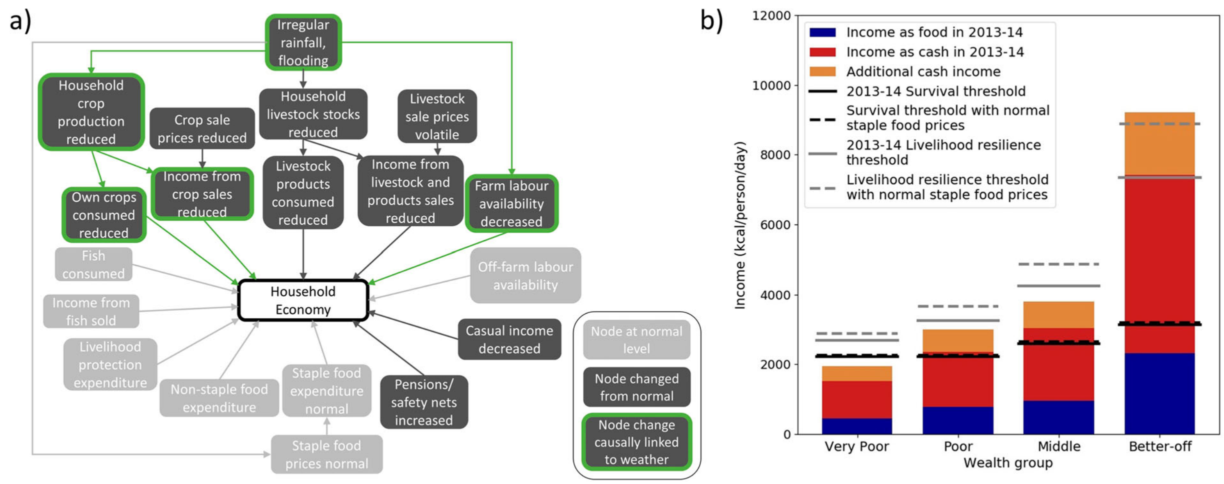

Figure 6. Normal staple food price counterfactual storyline. (a) network diagram as in Figure 4(a) but for the counterfactual storyline of normal staple food prices, (b) incomes and survival and livelihood resilience thresholds as in Figure 4(b) but with the effect of staple food prices being at 100%.

storylines, it is evident that the poor weather conditions were a much larger factor than the high staple food prices in explaining the challenging conditions for households during the 2013–14 consumption year, depicted in Figure 4(b). This motivates a more detailed examination of the vulnerability of the different wealth groups to weather-related drivers, which is done in the next section.

3.4. Thresholds

The impacts on households in 2013–14 (Figure 4(b)) were due to a combination of production and price changes. Understanding how drivers are linked together in the network (Figure 3(b)) allows us to see which nodes are likely to change simultaneously due to common drivers, and therefore what storylines of household impact are plausible. For example, a poor weather year would not reduce local crop production without also reducing on-farm labour opportunities. To illustrate the links between nodes with local weather as a common driver, we investigate how simultaneous changes in these nodes have different effects on households. We analyze how large the changes from baseline 'normal' conditions (2007–8) in each node or combination of nodes would need to be to lead to households falling below their livelihood resilience and survival thresholds, as shown in Figure 7. We first looked at each node that is influenced by the local weather individually (Own crops consumed, Income from crop sales, Own livestock products consumed, Income from livestock and livestock product sales, Farm labour). We then looked at the pairs with common drivers (Household crop production affects both Own crops consumed and Income from crop sales; Household Livestock affects both Own livestock products consumed and Income from livestock and product sales), and finally, at all five nodes together. All components of a category were reduced at the same rate, e.g. crop production was reduced by the same percentage for each crop. This is not an exact representation of how crop production is likely to be affected by the weather, as some crops will be more resilient than others, but is used as a demonstration here.

Taking the example of the Poor wealth group, because these households have relatively little dependence on crops sold,

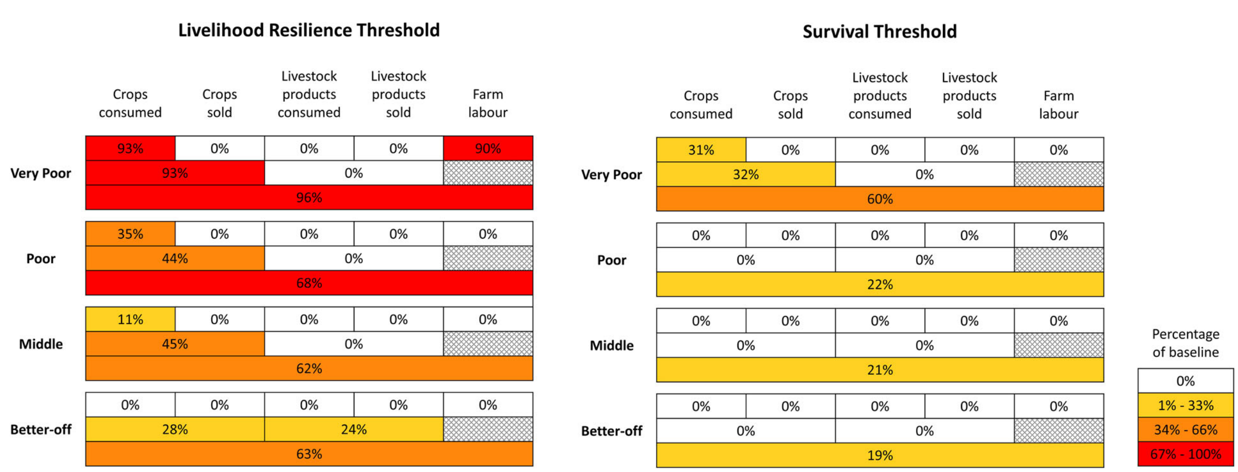

Figure 7. Percentages of baseline conditions which bring the different wealth groups down to their survival and livelihood resilience thresholds, for the nodes associated with the weather conditions. For each wealth group, the top line corresponds to individual nodes, with each node reduced separately; the middle line corresponds to combined effects of crops consumed and sold, and livestock products consumed and sold; and the bottom line corresponds to all weather-related nodes combined. Where nodes are grouped together, all change at the same percentage rate. The colour shading is indicative of the vulnerability level, with warmer colours corresponding to higher vulnerability since only a smaller reduction from the baseline conditions is needed to fall below the threshold.

livestock products consumed, livestock products sold, and farm labour, individually, those factors could each fall to zero (be removed from the budget) without the households falling below their livelihood resilience threshold (Figure 7). However, a fall in crops consumed to 35% of normal would mean falling below this threshold. Considering pairs of nodes, these households would fall below their livelihood resilience threshold if crops consumed and sold were both reduced to 44% of normal. Livestock products consumed and sold could be removed from the income together and households would remain above the threshold. When all five nodes are reduced simultaneously, they only need to decrease to 68% of normal levels for Poor households to fall below their livelihood resilience threshold. These decreases in individual and combinations of nodes leading to Poor households falling to their livelihood resilience threshold are shown in Figure 8, and illustrate the vulnerability of these households to weather-related shocks.

As expected, the better-off a household is, the larger the individual decreases in crops, livestock and farm labour they can withstand without falling below their livelihood resilience thresholds, as they are less dependent on these among other income sources. Indeed, Better-off households could lose each income source individually without falling below their livelihood resilience threshold. Other wealth groups require income from crop production, but can tolerate some reductions. However, reducing a household's crop consumption makes the household more dependent on market purchases, and exposes it to increased market prices if these occur.

Greater income reductions are required for households to fall below their survival thresholds. The Very Poor fall below their survival threshold if there are decreases in crops available for consumption to 31% of normal, or if all weather-related income sources fall to 60% of normal. Poor, Middle and Better-off wealth groups only fall below their survival thresholds if there are decreases across all the local weather-related nodes to 22%, 21% and 19% respectively.

4. Discussion

4.1. Food security impacts in Caprivi, Namibia

We have demonstrated the use of a storyline approach to understand local food security impacts from different drivers, using the case of the Caprivi region in Namibia. The impacts of shocks, such as a poor agricultural production year, differ depending on wealth group. Correspondingly, interventions have different effects. In 2013–14, poor crop production had large impacts for poorer households, while low sale prices had large impacts for richer households. This led to the Very Poor, Poor and Middle wealth groups falling below their livelihood resilience thresholds. Increasing off-farm labour availability had the biggest impact on Poor households, as this provides a greater proportion of their income. Reducing livelihood costs had a greater impact on the wealthier households,

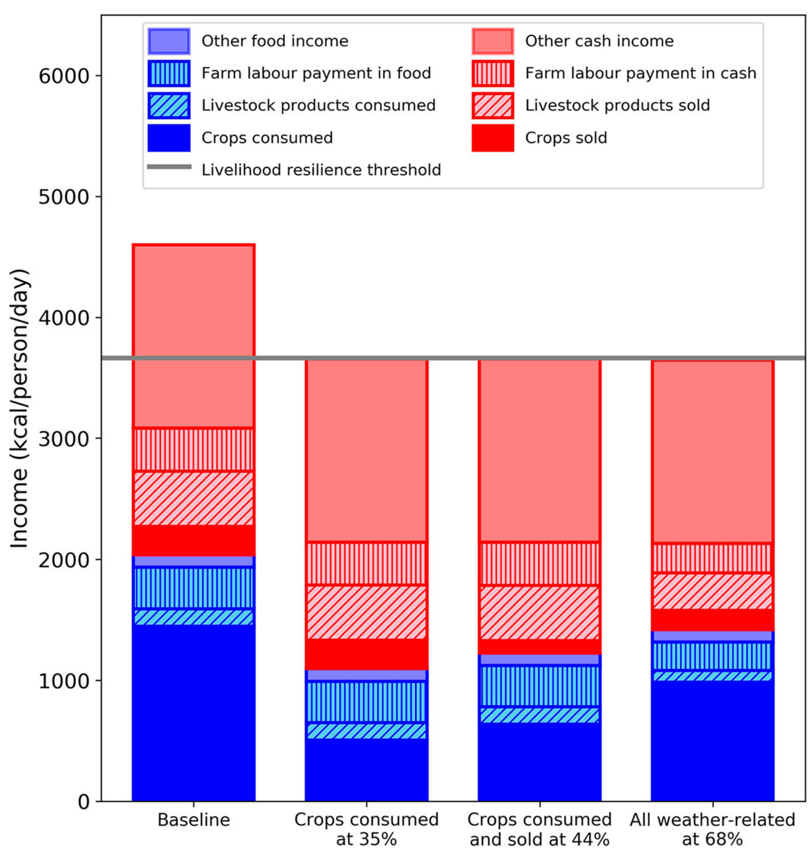

Figure 8. Poor household incomes from food and cash sources relative to the livelihood resilience threshold, for baseline conditions and changes in weather-related nodes reducing income to the livelihood resilience threshold as in Figure 7.

who typically have higher costs to maintain their livelihood standards. Very Poor households would have remained dependent on food or cash handouts even with the other interventions suggested. However, alternative actions such as subsidizing staple food purchase price would have been beneficial for this wealth group, as they typically purchase a large proportion of their food.

While the poorest will mostly (but not always, e.g. De Waal, 1989) be the most severely affected by shocks in a food security system, the impacts will vary between populations with different economies. Using the HEA methodology together with storylines of potential shocks, the interventions required to avoid the worst outcomes, specific to each population, can be determined.

This analysis also highlights the correlated impacts weather conditions have on household food security. Simultaneous decreases in crop production, livestock and farm labour lead to large impacts on a household's economy, from the Very Poor households who typically live very close to their livelihood resilience threshold, to the wealthier. Other changes, such as increased selling prices for crops and livestock, can partly compensate for these impacts if the buying prices do not also increase. Weather conditions will also have larger scale effects at national and international levels, affecting food availability and price (especially with the large proportions of cereals typically imported into Namibia) and labour availability nationally. These will propagate down to the local household level and have differing impacts across the wealth groups.

4.2. Storylines of future food security

Here, we have demonstrated the use of a network to better understand the impacts that occurred in the past and the effects of interventions. This same framework, however, can also be used to look at storylines of the future. These storylines could be different weather scenarios within a future climate. Mapping these through the nodes in the network to produce plausible food security storylines could use models where relevant, along with expert knowledge. For example, crop models can estimate crop production under particular weather conditions. The pathways can be associated with plausible policy actions which would mitigate any negative impacts. While what is plausible as a policy option is somewhat subjective, this approach does not have to be purely theoretical. Instead, people with expert understanding of the context and practical interest can provide information relevant to the decisions. Indeed, information generated using the HEA was intended to be used by policy makers with practical knowledge, and is currently used in this way. Considering future climate risk storylines is therefore a natural extension to its shorter-term use, as well as being a useful tool for modellers, crop scientists, and other researchers.

There are challenges when looking at climate change storylines in this context though. There is a mismatch between long-term climate projections and the short-term estimates of impact provided by the HEA, and modelling climate impacts decades ahead based on a recent year's economy is unlikely to provide reliable results. However, this may be sufficient to provide some information for policymakers, conditional on the current economy. For example, distinct possible future climate scenarios could be used, such as the three future climates for East Africa developed by the HyCRISTAL project (Burgin et al., 2019) which are characterized by different changes in temperature and rainfall. Crop models could be used to assess the impacts of the climate scenarios on different crops, and then the HEA data and household budget calculation used to assess the impacts on households. These discrete climate storylines would provide a way of characterizing the epistemic uncertainty, particularly at local scales where classical probabilistic uncertainty ranges are likely to be large. Policy options could then be considered, for example encouraging the use of different crop varieties where production is likely to decrease. Socio-economic storylines to characterize possible futures in the economy could also be combined with the set of climate storylines.

The network we have developed here focuses on a single agricultural year. However, it is also important to consider the impacts of recurrent poor years. If a household falls below their livelihood resilience threshold they may not be able to maintain their same livelihood standard to the next year. A household falling below their survival threshold will have to use coping strategies to survive, such as selling off assets, and so will have very little left for the next year. In this way chronic recurrent crises wear down households' resilience and their food security (Boyd et al., 2013). Storylines for longer term planning than a single year will need to take these potential accumulating impacts into account.

The network focusses on the household level and local weather for this example, but could also be extended to show linkages to national and international levels. The results we show of household impacts are conditional on the states of the nodes chosen, allowing us to make assumptions about larger-scale drivers. For example, we can condition on particular staple food prices, rather than modelling the drivers of food price. This is particularly useful in a case like this where we do not know all the drivers to predict food prices, but can produce storylines based on a range of possibilities. In another example, deterioration in the Namibian economy would likely affect the provision of pensions, with differing impacts across the wealth groups. Storylines characterizing scenarios with differing pension provision could be combined with other impacts such as changing food prices or crop production.

4.3. Storylines for decision-making

The uses we have shown for storylines reflect two of those presented by Shepherd et al. (2018): improving risk awareness and strengthening decision-making. We can use the network to characterize past events and to better understand the combinations of drivers that led to particular impacts. This may improve risk awareness more effectively than a probabilistic approach, which users can find difficult to assess and understand (Taylor et al., 2015), as risks are more readily perceived in an event-oriented manner (Shepherd et al., 2018) incorporating aspects of vulnerability (Dessai & Hulme, 2004). Decision-making can be strengthened through using this framework with policymakers to work backwards from the food security vulnerabilities of different wealth groups, combining information about local weather, production, labour and price conditions with possible interventions to show the impacts on households.

The approach also showcases how the effects of different policy options on household food security can be easily assessed, as it is straightforward to understand how the information was produced. All participants involved, including decision-makers, are able to understand how the storylines are developed and the uncertainty involved, and are therefore free to consider their value and disagree with the assumptions and outcomes if they wish. As more information becomes available about uncertain variables, more confident storylines can be developed and the range of the set reduced. We know the policy options described here are plausible because they are based on decisions that have been recommended or implemented in the past by those working in the specific context. This approach makes it possible to ensure the information produced is contextually relevant through working with local experts to understand the network of drivers of impacts and the types of policy options that would be relevant.

5. Conclusion

We have used the example of household food security in the Caprivi region of Namibia to demonstrate the role storylines can have in understanding local impacts from larger scale drivers and helping policymakers assess intervention options. We used a storyline of a historical event where floods destroyed crops to understand the impacts on local households in different wealth groups, and assess the impacts interventions would have had, highlighting the variations due to different sources of food and cash income. We then made sets of assumptions to produce counterfactual storylines, showing how the local impacts would have been different under good weather or normal food prices.

We have demonstrated the importance of understanding the network of drivers of impacts, and how drivers are linked by common parents, in producing plausible storylines for future planning. In this context, a household may be able to cope with losing an individual food or income source entirely, but these sources are not all independent. Decreases in all sources affected by the weather can lead to households across the wealth groups having to consider employing coping mechanisms.

Looking to future projections, this approach provides a distinct set of plausible storylines instead of propagated uncertainties from the global to local levels (Wilby & Dessai, 2010). This could provide a useful characterization of uncertainty for a range of climate change impacts experienced at the local scale. This alternative approach does not make predictions as such, but provides information and a space to consider future possibilities and potential actions associated with these. It is how the HEA has been applied in many countries across Africa to plan interventions (e.g. FEWS NET, 2020; Government of Malawi, 2005, 2016; Holzmann et al., 2008; Seaman et al., 2014), with storylines allowing decision-makers to assess local impacts and the effects of policy decisions, ensuring households are able to cope with changing weather conditions.

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